

2012 Year-End Report on Neurotechnologies for In-Vehicle Applications

**by Brent J. Lance, W. David Hairston, Greg Apker, Keith W. Whitaker,
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Army Research Laboratory

Aberdeen Proving Ground, MD 21005-5425

ARL-SR-267**June 2013**

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| 14. ABSTRACT This report provides a summary of the work and a highlight of the accomplishments performed by the U.S. Army Research Laboratory (ARL) on developing neurotechnologies for in-vehicle applications for the work period of 2012, the first year of the research program. The report will cover several aspects of the research program, including a newly funded ARL program in safe and wearable sensor technologies, a new Small Business Innovation Research program for evaluating electroencephalography sensor technologies, a joint ARL–U.S. Army Tank Automotive Research, Development, and Engineering Center experiment for translating current driver performance prediction technologies to real-world driving domains, the development of simulation technologies for researching driver performance, an evaluation of existing driver performance prediction technologies, and ARL's work on developing task-independent calibration techniques to use for individual Soldier performance prediction algorithms. | | | | | |
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1. Overview: Neurotechnologies for In-Vehicle Applications

1.1 Objective

This report provides a summary of the work performed by the U.S. Army Research Laboratory (ARL) developing neurotechnologies for in-vehicle applications for the work period of fiscal year 2012, the first year of the research program.

1.2 Program Overview

Vehicle survivability is an important issue in today's military. However, one of the most critical aspects of survivability is the performance of Soldiers operating the vehicles. In fact, recent analyses have revealed that motor vehicle crashes account for nearly one-third of U.S. military fatalities annually, including both privately owned and military motor vehicles. As a result, motor vehicle accidents are the leading cause of fatalities among U.S. military personnel (Krahl et al., 2010). Human errors are to blame in approximately 96% of all civilian crashes (Amditis et al., 2010) and drowsiness increases the driver's risk of a crash or near-crash by at least a factor of four (Klauer et al., 2006). These effects are likely to be accentuated in military vehicle environments because Soldiers perform high-stress missions across many time zones around the world for sustained periods. Often, Soldiers are deprived of sleep and have irregular sleep/work patterns (Mitler et al., 1988). Moreover, unlike most civilian and commercial driving, which is primarily concerned with mobility and safety, military driving involves the additional concern of security (McDowell et al., 2008).

As a result, ARL has undertaken research efforts to assess the state of human vehicle operators and integrate that state information into future vehicle systems. ARL's work will focus specifically on developing a testbed system that predicts and mitigates task performance decrements to optimize Soldier-system performance in realistic operational environments. Initial research will be focused on optimizing performance at driving tasks, while later work will attempt to generalize algorithms developed for driving tasks to additional Army-relevant tasks.

1.3 Approach

ARL's approach is to (1) translate current brain-state monitoring and performance prediction technologies to real-world domains, by evaluating the utility of the current technologies in progressively more complex and realistic conditions, and improve the technologies as needed to develop robust brain state detection and task performance prediction, and (2) enable the future fielding of these performance prediction technologies by performing the research to develop increasingly robust, higher resolution, and safe portable sensor technologies, while simultaneously developing improved tools for evaluating these new sensor technologies.

1.4 Report Overview

The remainder of this report will highlight ARL's accomplishments in the first year of the neurotechnologies for vehicle applications research program. The report is organized as follows: section 2 will briefly review state-of-the-art techniques for fatigue-based performance prediction. Section 3 will discuss a joint ARL–U.S. Army Tank Automotive Research, Development, and Engineering Center (TARDEC) experiment for translating current driver performance prediction technologies to real-world driving domains. Section 4 will describe simulation technologies developed for researching driver performance. Section 5 describes ARL's work on developing task-independent calibration techniques to use for individual Soldier performance prediction algorithms. Section 6 will describe a newly-funded ARL program in safe and wearable sensor technologies. Section 7 introduces a new Small Business Innovative Research (SBIR) program for evaluating electroencephalography (EEG) sensor technologies. Section 8 provides an evaluation of existing driver performance prediction technologies.

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2. Reviewing State-of-the-Art Techniques for Fatigue-Based Performance Prediction

2.1 Introduction

Degraded Soldier performance is an essential factor that can undermine U.S. Army efforts aimed at enhancing vehicle survivability. In particular, Soldier errors can lead to poor tactical decisions, which in turn might compromise an ongoing mission. In the case of military operators of both unmanned and manned vehicles, degraded performance can cause otherwise preventable accidents that might render a vehicle inoperable or, worse, lead to injury or death. Vehicle crashes account for approximately a third of all military fatalities each year, and a leading cause of motor vehicle crashes is fatigue. Recent fatigue management technologies (FMTs) geared toward monitoring and mitigating driver performance decrements have been shown to improve driver safety and survivability. To begin addressing this issue, ARL will require an understanding of currently available FMTs, as well as an understanding of what technologies will become available in the mid-term and long-term.

Houser et al. (2009), for example, evaluated the costs and benefits associated with lane departure warning systems and concluded that motor carriers purchasing this technology would likely prevent thousands to tens of thousands of crashes as well as net positive returns on investments in a five-year product lifecycle. For military applications, it is likely that even greater benefits could be obtained, in part because standard operating procedures could be implemented to ensure more complete integration of FMTs into all aspects of Soldier training, mission planning, and operational performance. If a robust and reliable FMT were to be deployed with crews serving military vehicles, the potential impact on accident reductions, enhanced situational awareness, and overall crew performance could be quite profound.

2.2 Method

ARL has conducted a literature and technology review to identify the current and soon-to-be-available FMTs for near-term integration into active safety technology programs for military vehicles. Because over 100 FMTs are either currently on the commercial market or are emerging from various stages of research and development, we have focused on a general overview of FMTs, bolstered with specific examples.

2.3 Results and Discussion

The literature review shows that FMTs can be generally categorized into one of three primary approaches: (1) vehicle-centered, (2) operator-centered, or (3) combination/hybrid approaches. Vehicle-centered technologies include any system that was designed to utilize data from operator-vehicle or vehicle-environment interactions, such as steering and lane-keeping, accelerating, braking, and encounters with objects or other vehicles.

Operator-centered technologies include any system that utilizes data from human operators and can be further broken into three subcategories: (1) biomathematical models of alertness, (2) fitness for duty testing, and (3) real-time monitoring technologies. Finally, hybrid approaches incorporate two or more of these approaches to provide a more comprehensive and robust system than a single technology used in isolation.

As a result, we conclude that a phased approach is likely the best way to incorporate these technologies. Near-term integration efforts should focus on the limited number of currently available and proven technologies, such as: the ASTiD* (Fatigue Management International, Birkenhead Wirral, UK) system, which integrates a biomathematical model of fatigue with signal processing of steering behavior; the Optalert† (Optalert, Melbourne, Australia) system, which predicts fatigue based on eye-tracking measures; or the SafeTraK (Takata Corp., Tokyo, Japan) system, which measures lane deviation using a small video camera. These three systems represent an important combination of vehicle- and operator-centered technologies that could account for a broader array of fatigue-induced issues than any one current system could manage on its own.

In a second medium-term phase, integration of these types of systems into a single system, such as the Cognitive Avionics Tool Set (CATS, Operator Performance Laboratory, University of Iowa), which is based on the fusion of multisensory operator-centric data streams, would enable increased potential for achieving greater robustness and reliability across a broader set of environments and operators. Finally, in the far-term, continued research at both basic and applied levels will be required to make FMT systems achieve higher reliability, validity, sensitivity, specificity, adaptability, compatibility, and user acceptability. We conclude that more successful future approaches will be those that integrate and fuse a variety of data at each level from human physiology and behavior to vehicle motion and mission performance. A more in-depth review of this work can be found in (Kerick et al., in press).

2.4 References

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* ASTiD is a registered trademark of Fatigue Management International, Birkenhead Wirral, UK.

† Optalert is a registered trademark of Optalert, Melbourne, Australia.

3. Translating Driver Performance Prediction Technologies to Real-World Driving Domains

3.1 Introduction

The Ground Vehicle Simulation Laboratory (GVSL) at the U.S. Army Tank Automotive Research, Development and Engineering Center (TARDEC) and the U.S. Army Research Laboratory (ARL)/Human Human Research and Engineering (HRED) Translational Neuroscience Branch performed a collaborative experiment, funded through the TARDEC In-house Laboratory Independent Research program, to conduct Soldier-centric ground vehicle research on the utility and design of brain computer interaction technologies in future Army crew stations. In particular, the goal of the experiment was to expand upon prior work published by academic partners in the Army's Cognition and Neuroergonomics Collaborative Technology Alliance by investigating the capability to generalize a neurally-based driver performance prediction methodology (Lin et al., 2005) from a simple single-task laboratory environment to a multitask Army-relevant driving scenario. To collect the data, the project utilized TARDEC's Ride Motion Simulator (RMS) and its real-time simulation environment to create an Army-relevant task/scenario and environment and to control run-to-run variability.

This experiment will provide basic research and proof-of-concept results to support the development of testbed Warfighter technologies that use neural signals to predict and mitigate task performance decrements to enhance Soldier performance during manned ground vehicle operations. Moreover, generalization of this technology has significant application potential to similar long Army-relevant vigilance tasks, such as robotic teleoperation or supervisory control.

The method extended the experiment and analysis described in (Lin et al., 2005) to a more complex and realistic Army-relevant driving task. Lin et al.'s (2005) task consisted of driving down a long straight traffic-free road on a six-degrees-of-freedom ride motion platform. Periodically, lateral forces were applied to the vehicle, pushing it sideways off of the road. By using the frequency power-spectra of neural signals collected through electroencephalography (EEG), Lin et al. (2005) were able to predict the driver's reaction time to the lateral perturbing force. While performance of this system at this task is quite good, it is not clear how well this technique will generalize to more realistic Army-relevant environments. We have extended this research through enhancing the task complexity by studying driver performance as part of a military convoy. Instead of only one vehicle in the experiment, there was also an automated convoy leader in front of the subject's vehicle and an added task of maintaining proper following distance to the convoy leader.

3.2 Method

Fourteen subjects drove down a very long straight highway during a single 45-min driving session. Subjects were tasked with staying in lane and maintaining following distance to the lead vehicle. Approximately every 10 s either a lateral or longitudinal perturbation occurred. A lateral perturbation consisted of a strong lateral force pushing the vehicle to the left or right. A longitudinal perturbation consisted of either a sudden slow down or speed up by the lead vehicle. Two metrics of driver performance were utilized. The first was defined as “lane deviation,” the distance from the center of the vehicle to the center of the driving lane. The second was defined as “following distance deviation,” the distance from the center of the vehicle to the following distance the subjects were required to maintain. Both performance metrics were measured continuously at approximately 100 Hz. Throughout the driving session, 64-channel EEG signals were recorded at 2048 Hz.

3.3 Discussion

Data collection has been completed and data analysis is currently in progress. TARDEC is analyzing the behavioral data (e.g., steering behavior and following distance) collected during the experiment looking for correlations between driver reactions to the longitudinal and lateral perturbations. Simultaneously, ARL is analyzing the neural data, attempting to predict Soldier reaction time to the lateral and longitudinal perturbations using Lin et al.’s (2005) algorithm on the EEG data. In addition to this primary experiment, ARL also provided expertise and support for the analysis of a joint GVSL and Joint Program Office-Mine Resistant Ambush Protected Vehicles experiment focused on identifying driver task load in real time.

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4. Simulation Platform for Developing and Evaluating Neurotechnologies for In-Vehicle Applications

4.1 Introduction

The U.S. Army Research Laboratory (ARL) contracted the DCS Corporation to develop a flexible simulation testbed system for testing driver performance prediction for basic science experiments and neurotechnology system development. The initial system consists of two primary components: (1) a simulation environment that is user-configurable, allowing for a large variety of scenarios to explore vehicle driving performance, and (2) an Arduino-based system that synchronizes simulation events and subject responses with physiological indicators such as electroencephalography (EEG) and eye-tracking.

4.2 Configurable Simulation System

The simulation system is based on the SimCreator system (Real Time Technologies, Dearborn, MI) to provide real-time simulation of driving tasks. The configurability of the system arises from a tile-based paradigm that generates a driving terrain database of any desired length by assembling a number of road tiles (see figure 1).

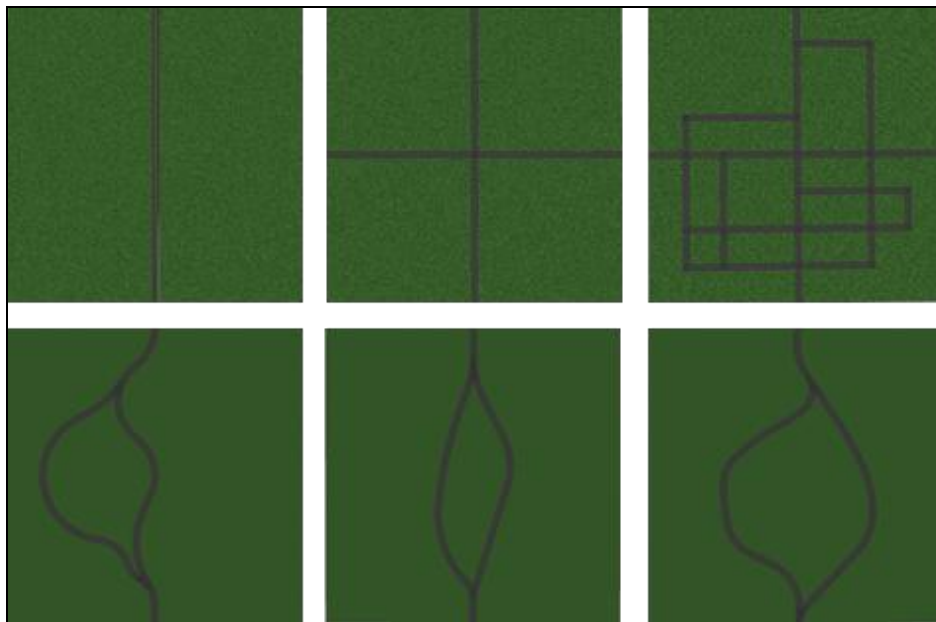


Figure 1. Example road tiles for the driving simulation system.

Each tile has one or more four-lane road segments (the left two are oncoming and the right two are in the direction of travel) where the road segments enter and exit each tile in the center of the edge. Each tile has been carefully surveyed to allow the real-time provision of standard driving performance metrics, such as lane deviation, time-to-contact, etc. Detailed data logging provides

a capability to more thoroughly assess these and other driving performance metrics offline during post-tests analyses. In addition to the road tiles, the system allows the user to configure several driving events within the tiles. Such events currently include wind perturbations that push the vehicle sideways off the road; speed limit signs; vehicles driving in the oncoming lanes, in the direction of travel, or across the road at intersections; pedestrian traffic; and construction zones. For each event, the user can control the number of entities, event onset and offset, event location, and the motion path (for moving entities).

To support the broader goals of allowing basic science experiments and neurotechnology design, the simulation system was designed from the ground up for integration with standard physiological data acquisition systems, such as EEG, eye-tracking, electrocardiography (EKG), electrodermal activity (EDA), and respiration. All signals are synchronized using an Arduino-based synchronization system and recorded on locally networked PCs.

4.3 Arduino-Based Simulation Synchronization

Time synchronization across measurement devices in neuroscience experiments is critical for the analysis and interpretation of datasets, in particular when performing EEG studies. Currently available commercial options are expensive and often limited to the integration of specific sensors. The aim of this project was to develop a general-purpose low-cost synchronization solution that could support integration of a wide variety of digital and analogue sensors with submillisecond time resolution.

The resulting temporal synchronization device (TSD) is built on the Arduino Mega platform, a low-cost open-source easy-to-use microcontroller, in conjunction with a custom-built Arduino Shield expansion card. This device provides a general-purpose solution for synchronizing multiple supplementary sensors with physiological data. The device works by sampling all of the sensors it is integrating as well as a pulse signal sent by the EEG system. It integrates the collected data with the pulse signal and streams it to a host computer via a USB serial connection. The current sensor setup uses 23 of the TSD's input ports and streams the data to the host machine at 1024 Hz. As a result, the TSD could integrate additional sensors without dropping the level of synchronization accuracy.

The TSD provides a general-purpose low-cost solution for synchronizing data and time triggers from multiple sources with a high degree of accuracy, allowing for the integration of multiple data collection devices with differing types of stimuli, including stimuli presented in generally harder-to-synchronize domains such as virtual environments or simulation engines.

4.4 Conclusion

In total, the system provides the capability for formal data collection events, either for basic science experiments or as technology assessment and prototyping. All data, including driving performance, simulation behaviors (i.e., entity- and tile-based information), and physiological measures, are synchronized to enable precise assessment of relationships between brain and

behavior. In addition, the system is completely configurable such that analyst-level users may completely design test scenarios through an automated software toolset. Options include specification of tile sequences, event dynamics, as well as custom user-specified events. Overall, such a system allows for the specification of experiment requirements of a broad range in terms of levels of complexity (from simple straight roads with no traffic to a complex urban environment with both vehicle and pedestrian traffic), while maintaining an ability for experimenters to derive highly precise data regarding operator performance and psychophysiological state.

5. Task-Independent Calibration Techniques for Individual Soldier Performance Prediction Algorithms

5.1 Introduction

There are numerous challenges to effectively using neural signals in brain-computer interaction (BCI) technology development. One of the primary challenges lies with the individual differences in neural or physiological response to tasks or stimuli. In order for the performance prediction algorithms described in section 7 of this report to address these individual differences, a calibration period of training data needs to be collected from each individual. However, the time spent collecting this data is likely to decrease the utility of these systems, slowing their rate of acceptance.

Currently, Lin et al.'s (2005a) algorithm requires a calibration period of at least 15 min of driving in a simulated environment to obtain the training data needed for predicting driver performance. However, this is a less than ideal solution. If Soldiers could use a general handheld calibration app for a few minutes instead, training data acquisition would require considerably less expense. In addition, it is more likely that this calibration solution will generalize to additional tasks beyond driving

5.2 Methods

The U.S. Army Research Laboratory (ARL) has implemented two general calibration tasks into an Android device. These two tasks are the continuous tracking task (CTT) and the psychomotor vigilance task (PVT), both of which have prior research showing that performance on these tasks may be useful for predicting performance at driving tasks. It has been shown that the same data processing methods for predicting performance at the Lin et al. (2005b) driving task are also effective at predicting performance on the CTT task (Makeig and Jolley, 1995). The CTT consists of performing a “bubble level” style task, where the user attempts to tilt the Android device to keep a small moving circle inside of a larger static circle. Periodically, a random perturbing force is applied to the small moving bubble circle, pushing it out of place. The Android CTT app measures and records user score and response times. PVT performance has been shown to be closely associated with the fatigue level of the user, which can be used to predict performance at driving tasks (Dinges and Powell, 1985; Balkin, 2000). The PVT consists of a basic vigilance task, where the user watches the screen of the device looking for a rarely occurring stimulus. When the users see the stimulus, they respond by touching the screen. The PVT app also measures and records user score and response times.

5.3 Discussion

The implementation of the CTT and the PVT, and recording score and response times on an Android device, has been successful. Current work focuses on implementing EEG recording

capabilities for the Android platform and synchronizing those capabilities with the CTT and PVT apps. In the future, we will use the recorded EEG and behavioral data during the CTT and PVT tasks to evaluate their utility as calibration mechanisms for predicting performance at driving tasks.

5.4 References

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6. Safe and Wearable Sensor Technology

6.1 Summary

6.1.1 Overview

There is extremely strong interest in moving neurotechnology out of laboratory settings, and into real-world every-day environments where behavior can be measured in its native setting. Support for the importance of this idea, and the extensive benefits gained from it, have come from as high as the Office of the President (National Science and Technology Council, 2009). Meanwhile, the National Research Council has strongly encouraged the U.S. Army to develop sensor arrays capable of accurately detecting and quantifying a Soldier's physiological and cognitive states while performing mission-related tasks in a field environment (National Research Council, 2009). One promising method for doing this is through electroencephalography (EEG), a noninvasive method to measure brain activity, as characterized by the electrical potentials observed at the scalp that provide high temporal resolution consistent with the time scales of brain processes. EEG is the most likely method for developing technologies based on brain activity due to the low cost and portability compared to alternative brain-imaging technologies such as magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI) systems, both of which require a room-sized device that costs hundreds of thousands of dollars and a completely stationary user.

However, current EEG technologies are time consuming to prepare, cannot be placed in vehicles due to the lack of portability owing to the necessity for the electrodes to be physically tethered to a signal amplifier, and the metal electrodes may present safety concerns in test, research, and evaluation environments where dynamic body motions and impact events may occur. For example, typical laboratory EEG systems involve attaching as many as 256 small tethered metal (e.g., silver chloride) electrodes to the scalp as well as the application of conductive gels to reduce skin-electrode contact impedance in order to obtain adequate signal quality. As a result, integration of BCI technologies with in-vehicle systems is severely challenged by the form factor of contemporary sensory systems. In order to avoid these challenges, vehicle system developers will require easily wearable EEG systems that are wireless, comfortable, robust, safe, and validated to work within a number of environments.

Currently, the U.S. Army Research Laboratory (ARL) is addressing this need through research focusing on two specific aspects of wearable EEG technology: (1) dry, comfortable, impact-safe electrodes with flexible biosensing electronics, and (2) evaluation technologies to serve as a standard for testing new hardware approaches.

6.1.2 Dry, Impact-Safe EEG Electrodes

In 2011, ARL and Cognition and Neuroergonomics (CaN) Collaborative Technology Alliance (CTA) partner National Chiao-Tung University (NCTU) in Taiwan developed a novel EEG sensor design comprised of a polymer foam substrate covered by a conductive fabric (Lin et al., 2011, figure 2). The foam-based sensors were shown to provide signal quality comparable to traditional, laboratory-standard wet (gelled) electrodes while having the benefits of easy and fast application, high conformity with the scalp surface, improved comfort and performance during long-term wear (about 5 h), and the potential to provide increased safety in dynamic measurement conditions. The authors also indicate that the sensor technology is cost-effective, with per unit costs for sensor fabrication of about U.S. \$0.30.

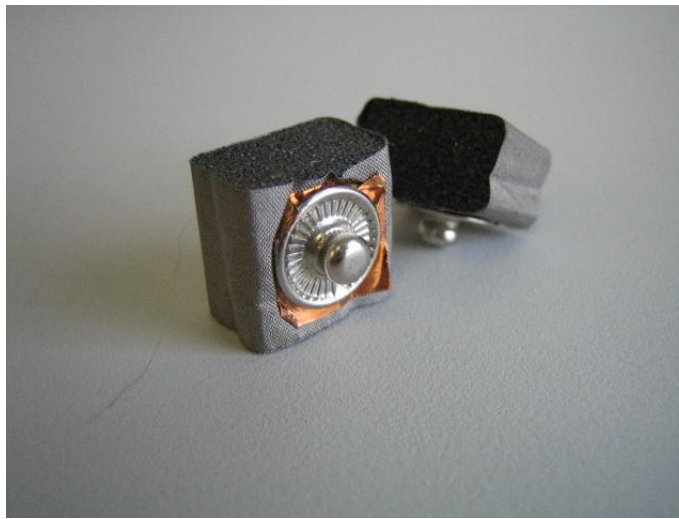


Figure 2. Dry, conductive-fabric EEG electrode.

The performance of the foam-based EEG sensors was then evaluated in a standard laboratory task and in a brain-computer interaction technology (Liao et al., 2012a) that allowed real-time control of a simple video archery game. The accuracy of shots in the game was controlled by the users' ability to produce a "mentally focused" state, which was operationally defined based on previous research results as the inverse of the average EEG spectral power in the 8- to 12-Hz frequency range.

In addition to the development of these sensor technologies, NCTU, ARL, and University of California San Diego (UCSD) partners also provided a survey of current biosensor technologies and provided expert analysis and prediction of future BCI research and development efforts (Liao et al., 2012b).

6.1.3 Flexible Biosensing

In order to be effective and comfortable, EEG systems must stretch with Soldier motions without hindering movement or otherwise negatively impacting the Soldier's mission or safety. Standard rigid electronics have well-understood signal filtering characteristics but significantly decrease the flexibility and comfort of electronic sensors when in close proximity to the body. When deployed in wearable systems, rigid components can also compromise survivability, particularly if employed inside protective armor. Pliability of the material solution is important for increased Soldier comfort and safety on the battlefield.

To address this issue, ARL, through collaboration among its Human Research and Engineering Directorate (HRED), Weapons and Materials Research Directorate (WMRD), and Vehicle Technologies Directorate (VTD), has initiated a new program focused on the development of pliable, stretchable conductive materials that have highly predictable and stable conductance over a range of deformation. During fiscal year 2012 (FY12), this group manufactured a prototype array of stretchable EEG electrode wire conductors in a format similar to that of the Advanced Brain Monitoring X-10 EEG system (figure 2). These stretchable wires were embedded in a stretchable acrylic coating with exposed ends for connecting sensor pads. This prototype yielded positive results, demonstrating comparable signal attenuation to a state-of-the-art laboratory EEG lead when under 20% strain.

However, one pitfall discovered in this initial approach was that the nonconductive outer coating of the stretchable wire array poses a barrier to direct contact with the wearer (which is typically bridged via electrolytic gel). Follow-on efforts showed that one viable approach is to add a crimp-on style metal snap that penetrates the material and provides media for connecting a separate electrode connector matching the format of the dry, impact-safe EEG electrodes under development through the CaN CTA. Initial results indicate that this method provides an acceptable conductive connection but additional testing is needed to determine whether or not the crimp will lead to tearing of the stretchable material with repeated use. Also during this fiscal year, funding was applied for and granted through the ARL Director's Research Initiative (DRI) program, securing support for FY13 through FY15. A more in-depth review of this work follows.

6.2 Introduction

There is a current limitation in our ability to assess cognitive and other brain functions within real-world, dynamic Army environments. This is due in part to a lack of tools that are logistically pragmatic or even safe to use in operational settings. Recent advances in materials science leading to conductive yet pliable and stretchable materials suggest the opportunity for revolutionizing the types of hardware that may be used for neurocognitive assessment in the future. This report describes the background, initial efforts, and near-term plans of a new effort (begun in FY12) for leveraging these advances for developing stretchable, deformable conductors and electrode interfaces to be used in EEG.

6.3 Background

The National Research Council has strongly encouraged multiple branches of the U.S. armed forces to develop sensor arrays capable of accurately detecting and quantifying a Soldier's physiological and cognitive states while performing mission-related tasks in a field environment (National Research Council, 2009; National Research Council, 2012). In order to be effective and comfortable, such arrays must accommodate the full range of Soldier motions without hindering movement or otherwise negatively impacting the mission or safety of the Soldier. Additionally, they must be pliable and deformable to mitigate potential safety concerns from ballistics or other impact injuries. Meanwhile, most biosensing modalities such as electrocardiography (EKG) or EEG involve measuring extremely small voltages at the skin-sensor interface (e.g., μV for EEG or mV for EKG), necessitating a sensitivity to miniscule changes in amplitude. As a result, going from the "bench to the battlefield" requires novel technologies to observe bioelectronic activity in real-world environments. Over the past five years, foundational steps have been taken toward this end through funding by ARL, the National Institutes of Health (NIH), the Defense Advanced Research Projects Agency (DARPA), and private industry (Liao et al., 2012b). Even with these investments, significant conceptual progress in both hardware and software needs to be accomplished to develop suitable capabilities to enable measurement of brain and body function in Warfighter operational environments.

The combat environment is a unique application for biosensing, which poses challenges to safety and comfort not encountered in other circumstances. According to personnel in ARL's WMRD who design prototype helmet systems, a combat-ready EEG system must be made of reconfigurable deformable components inside of the helmet system. To the best of the authors' knowledge, these two features are not part of any current development projects by any agency.

Standard rigid electronics, such as stranded-fiber or stamped-metal conductors, have well-understood signal filtering characteristics but significantly decrease the flexibility and comfort of electronic sensors when in close proximity to the body. When deployed in wearable systems, rigid components can also compromise survivability, particularly if employed inside protective armor (e.g., see figure 3). Pliability of the material solution is important so as not to compromise Soldier safety on the battlefield.



Figure 3. Current state-of-art in EEG technology. Left image shows configuration and labor-intensive setup. Right image illustrates the potential discomfort and temporary skin deformations associated with extended use.

As an alternative, the class of electronics known as “stretchable electronics” holds promise for this area. It is distinguished from materials known as “flexible electronics” by three fundamental differences: (1) an order-of-magnitude increase in the spatial scale of the deformation, (2) a resulting complex nonlinear shift in passive electronic behaviors (resistance, capacitance, and inductance), and (3) the potentially large resulting shift in signal filtering characteristics.

Pliable, stretchable electronic devices have only recently become possible due to advances in materials, including those made by ARL/WMRD with the development of soft mesoscale polymer composites capable of maintaining low levels of signal attenuation (less than 3 dB) while subjected to biaxial hyperelastic stretching (see figure 4). The data was acquired with Agilent E5061B LF-RF Impedance/Network Analyzer over frequency range of interest for EEG using the S_{21} series-through method. Sophisticated and unique new electromechanical characterization techniques were recently developed by ARL’s VTD that allow us, for the first time, to make accurate measurements of the influence that very large biaxial strains, frequency, temperature, and material type have on stretchable electronic signal attenuation and filtering characteristics (Slipher et al., 2012).

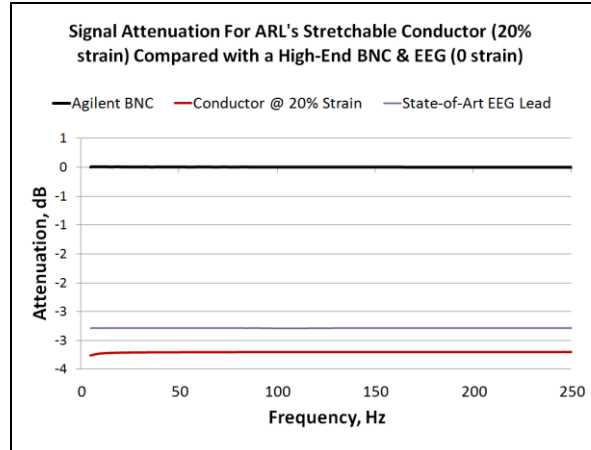


Figure 4. Recent experimental data acquired by ARL/VTD using the proposed experimental techniques on initial material samples provided by ARL/WMRD. Signal attenuation for ARL's stretched conductor at 20% strain is comparable to a state-of-the-art EEG lead.

6.3.1 Program Goals

We are leveraging these recent developments ongoing within WMRD and VTD to meet emerging mission requirements for fieldable biosensing arrays under development through HRED. Our goal is to develop spatially distributed and tunable, stretchable conductors for transmitting/filtering signals from biological sensors to data acquisition devices (e.g., EKG or EEG) for the purpose of fielding ruggedized Soldier biosensing arrays. There are three principal scientific challenges that we will address in this research program:

1. Materials must maintain consistent signal attenuation when conductors are subjected to deformations such as those that can be anticipated in a high-mobility environment instead of increased attenuation as is more typical.
2. The appropriate impedance must be maintained for dry contact electrodes interfacing with human skin and subjected to potentially large deformations in order to maximize biosignal throughput under field conditions.
3. Material-material interfaces will have to be designed in a manner that establishes an electrical and mechanical connection between two potentially dissimilar stretchable conductive materials, yet minimizes fatigue failures due to large strain gradients at the interface.

6.4 Program Activity During FY12

As a new program beginning quarter three (Q3) FY12, the primary goal for this year was to establish material development methods that would be most appropriate for EEG-type devices, establish a research plan, and secure funding for future efforts. Description of development and testing efforts follow. Proposals for both DRI and Director's Strategic Initiative funds were submitted, with funding granted through the DRI mechanism to provide support beginning FY13–FY15 (Slipher et al., 2012b), which also facilitated planning for future work.

6.4.1 Pliable Conductive Polymer Production

6.4.1.1 Replacement EEG Electrode Tips

Initial effort focused on developing material suitable for EEG electrode tips, which must be pliable to provide comfort and safety for long-term use on the scalp but also maintain consistent high conductance even when deformed by pressure from mounting the system on the head. Electrode tips were fabricated by dispersing carbon black into a poly-dimethyl siloxane (PDMS) matrix. The PDMS matrix is produced through reaction of a vinyl-terminated PDMS with a tetrafunctional silane cross-linker in the presence of a platinum catalyst. This chemistry is advantageous for these applications for two reasons: (1) there are no byproducts from the cross-linking reaction, resulting in minimal cure shrinkage, and (2) the end-linked functionality provides the ability to systematically tailor the mechanical properties over a wide range of modulus to provide the desired response and offset the impact of the carbon black addition. The conductivity of the composite material can be tuned by changing the carbon black loading.

Carbon black was mixed along with the PDMS network precursors using a Resodyn resonant acoustic mixer at a power of 60 dB for 5 min. The mixture was then poured into the mold and degassed via vacuum to remove the bubbles incorporated during the mixing process. The degassed materials were placed in an oven at 72 °C for 3 days to provide complete cure.

6.4.1.2 Stretchable Wire Conductors

A second effort addressed the substrate for wire conductors, for which a carbon-black/DPMS matrix would not be suitable. Conductors were fabricated by incorporating nickel-coated carbon fibers (NCCF) into a thermoplastic elastomer polymer using twin-screw extrusion. The thermoplastic elastomer matrix provides the ability to melt and reform the material using heat or dissolution in a solvent. The material was compounded in a DSM conical twin-screw extruder (DSM Resolve, Geleen, The Netherlands) at 200 °C and 50 rpm for 15 min and then extruded through a 3-mm cylindrical die. The extrudate was cut into an approximately 150-mm length and melt-pressed at 160 °C and 90 kN for 5 min to produce a uniform sheet. The sheet thickness was controlled by placing metallic spacers between the melt press platens. This allows for the production of large conductive elastomer sheets. For example, this initial study utilized conductive sheets about 250 mm × 250 mm × 175 μm and exhibited an end-to-end resistance of

about $145\ \Omega$ (about $6\ \Omega/\text{cm}$) (figure 5). When subjected to an equibiaxial strain, the stretchable conductor material was observed to initially increase conductivity. This increasing conductivity with strain reached a peak value at around 20% area strain, with a measured resistance of about $3.4\ \Omega/\text{cm}$. We believe that by tuning the properties of the mesoscale composite, the conductivity response to strain can be tailored to give a desired response as required for a given end use. For reference, moisturized EEG leads have a measured conductance of about $2\ \Omega/\text{cm}$. The conductor material was cut to the desired geometry using a commercial laser cutter. Use of the laser cutting equipment employed to date limits resolution for surface geometries to greater than $250\text{-}\mu\text{m}$ feature size; however, this is within the range necessary to mimic current EEG electrical components.

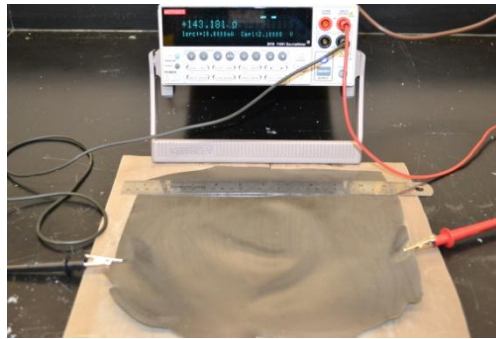


Figure 5. A conductive elastomeric sheet measuring about $250\text{ mm} \times 250\text{ mm} \times 175\ \mu\text{m}$ prior to laser cutting.

6.4.2 Production/Testing of Prototype Devices

Three different types of early prototype conductive polymer devices were produced as an initial trial application for the existing EEG systems.

6.4.2.1 Replacement EEG Electrode Tips

Electrode pads were made to replace the standard saline-soaked felt pads used in the Emotiv Epoc EEG system. Replacement tips were made using carbon black substrate mixed with PDMS, with the target impedance of the material set to match that of the manufacturer's pads (when soaked). The resulting pads were fairly soft and pliable. Initial testing showed that although the conductivity was approximately equivalent, it was extremely sensitive to compression and direction of surface contact such that slight deflections greatly increased the signal-to-noise ratio (SNR). It was determined that this approach (carbon black with DPMS) is not suitable for this application and would likely not address challenge no. 1 (page 17). As a result, alternative methods will be explored that will yield better consistency across contact axes.

6.4.2.2 Stretchable Wire Conductors

A set of EEG electrode wire conductors were made in a format similar to that of commercially available low-density EEG measurement system (Advanced Brain Monitoring X-10) and

embedded in a stretchable acrylic coating. Because this style system uses open-cell foam gel-filled pads to connect to the wire strip, similar exposed ends were left on the prototype strip (figure 6). This prototype yielded positive results, with conductance remaining broadly within the target range for a stretch of approximately 10%. However, while this provides evidence of successfully addressing challenge no. 1, it was evident that the native outer coating of the elastic conductor poses a barrier to direct-contact connection and will require future effort on the interface between the material and connections (challenge no. 2).

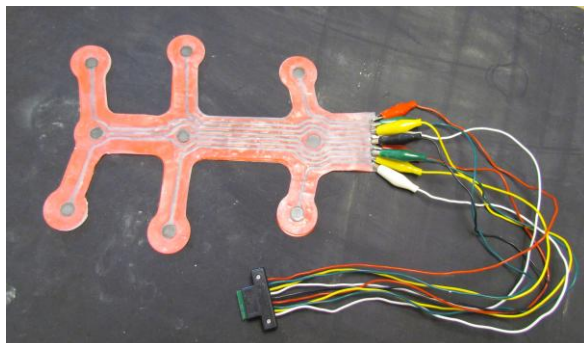


Figure 6. WMRD/VTD/HRED/Sensors and Electron Devices Directorate cooperative development of a stretchable EEG monitoring device.

6.4.2.3 Crimp-on Connectors With Stretchable Conductors

A crimp-on style metal snap was attempted as an interface between current “dry” electrodes (in development through CaN CTA) and stretchable conductive media. Initial attempts suggest that this method works for penetrating the outer layer of the media and makes a good conductive connection. Future work will need to consider whether the penetration caused by the crimp will lead to tearing of the material with repeated use.

6.5 Conclusions and Continuing Efforts

We feel that the flexible conductive materials currently under development in ARL-VTD and WMRD hold promise for the application to EEG or similar biosensing modalities, providing a pathway to equipment that is more comfortable and safe for the user in operational environments. Based on the initial tests described here, this application seems feasible for the materials and methods currently in development. However, considerable effort remains before this technology can be used in a reliable, repeatable manner for EEG. For example, the rapid change in conductance that occurs with compression or stretching will have to be reduced so that small fluctuations do not dramatically affect the measured EEG signal.

Efforts from this year provided guidance on which material methods may, and may not, be suitable for future investigation. For instance, carbon-black-laced DPMS was deemed an unlikely candidate, while the NCCF approach appears to hold promise. Based on this, continuing

and near-future efforts on materials development include first determining the critical factors within the NCCF-based approach that will improve performance for this application. Proposed methods include examining the factors that impact the ability of adjacent particles to slide in a polymer matrix, exploiting additives to decrease the surface friction, computational modeling of particle-particle friction in a polymer matrix, and exploiting particle-polymer interaction and polymer microstructure to tailor the electrical response of the material. Meanwhile, we will be developing processing approaches to expand integration into devices, a necessary step for building future prototype devices such as an EEG system. Finally, as full-scale prototype device components are fabricated, they will be tested in conjunction with conventional and current-development EEG systems to assess efficacy against standard hard-conductor approaches.

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7. Technologies for Evaluating EEG Capabilities

7.1 Summary

Contemporary systems used for electroencephalography (EEG) data collection are extremely sensitive to influence from electromagnetic interference (EMI) and other nonbiological external sources of noise. In a vehicle environment, this may arise from the vehicle engine or electrical system, communications equipment, or the vibration of the vehicle. These can cause artifacts and distortions that make the data difficult or in some cases even impossible to interpret. As neuroscience experiments move from the laboratory to the field, the environment becomes less controlled and less measurable, introducing novel sources of noise and error to the measuring devices. However, if environmental factors are known, as well as how they impact the recorded data, then many sources of error can be accounted and compensated for. One way to distinguish the externally driven noise sources from naturally occurring brain signals is through measurement of a standard model within the various target environments. At the moment, no standard model exists that can replicate human EEG-like signals in a medium similar to the human head, forcing most system designers to use actual humans as the source of test data. However, this approach is fraught with challenges, such as within or across person variance and lack of a strong known signal to serve as a ground-truth comparison.

To address this, the U.S. Army Research Laboratory (ARL) has initiated a Small Business Innovative Research (SBIR) project (A10-066, “Neurological Simulator for Applied Data Collection”) to leverage the innovation available through multiple small companies motivated by this opportunity. The primary goal is to develop a model human head that will replicate the electrical conductivity of the human head and provide the opportunity to create signals analogous to human brain activity. These signals can then be measured with standard EEG equipment, allowing the opportunity to provide a “ground truth” signal. Efforts from fiscal year 2012 (FY12), performed by Physical Optics Corporation, CFD Research Corporation, and Creare, Inc., focused on research into materials and potential design schemes, as well as development of initial prototype “phantom” devices delivered for testing to ARL (figure 3). A more in-depth review of these efforts is provided in the appendix.

This EEG phantom will provide ARL with several important capabilities for developing and evaluating wearable EEG technologies for real-world in-vehicle environments. First, it will allow us to quantify the amount of artifact and noise introduced into an EEG recording in a real-world vehicle system by using EEG to record a known signal from the phantom in both controlled laboratory and in-vehicle conditions. We can then analyze these recordings and quantify the difference, allowing ARL to develop or adapt capabilities to address these differences.

Second, the phantom will allow us to evaluate new and existing EEG technologies by recording known signals from the phantom using a variety of technologies and analyzing the resulting data to directly compare their performance.

7.2 Introduction

Currently, there is much effort underway to develop physical and computational tools for measuring brain activity outside of restricted laboratory environments. Unfortunately, there is no standard way for testing or validating these tools, due in large part to a lack of a standard “model” of brain activity that can be used as a known-quantity standard for comparison of either some putative tool or nonsignal noise emanating from the environment. The work described here reflects efforts to construct, validate, and use a novel “phantom” device for EEG equipment and algorithms. While much of the initial design and fabrication work is carried out via the U.S. Army SBIR process, testing, validation, and use of the device is occurring within ARL as a joint effort between ARL and SBIR contractors.

7.3 Background

There is a great deal of current work in the human performance arena that focuses on the application of cutting-edge neuroscience tools to real-world operational environments. This includes the integration of EEG or other measures of nervous system state with other sensor systems during specific Soldier activities. However, environmental conditions and electrical noise can adversely affect the collection of usable physiological and neurological measurements within real-world scenarios. As neuroscience experiments move from the laboratory to the field, the environment becomes less controllable by the operator, introducing novel sources of noise and error to the measuring devices. This can be problematic, but if environmental factors are known, many sources of error can be accounted and compensated for in experimental design, recording equipment design, or artifact modeling during online and offline data analysis. Likewise, similar techniques can be used for testing novel recording equipment or signal detection software tools.

One way to tease apart externally driven noise sources from naturally occurring and expected brain signal is through measurement of a standard or known-quantity model within the various target environments. At the moment, however, no standard model exists that can replicate human EEG-like signals within a physical structure that is similar in size, shape, and consistency to the human head. While there currently are a number of computational models outlining the conductive properties of brain matter, skull, and skin, no physical models are commercially available that also have analogous conductive properties. Likewise, the few physical, conductive models or “phantoms” discussed in academic literature (e.g., Gavit et al., 2001; Leahy et al., 1998; Looi and Chen, 2005; Miller et al., 2000) or made in a handful of laboratories either have not been created in an appropriate shape for use with complete conventional EEG caps or soldier headgear. Being structured as such would enable use as a benchmark for typical off-the-shelf cap-based EEG systems.

To address this deficit, an innovative system is needed that will replicate signals analogous in size and scope to human brain activity, which can in turn be measured with standard EEG equipment, allowing the opportunity to provide a true “ground truth” signal. In order to properly simulate the perturbation in measurement of real signals generated by human participants within varied environments, the model will have to be physically/conductively analogous to the human skull, scalp, and internal structure to functionally replace a human during experimental setup and testing and contain multiple sources for creating EEG-like signals from distinct interior points.

A phantom device such as described above has use in a wide range of applications (from validating lab or medical grade EEG systems to testing unknown environments or training new personnel); as a result, there is a high potential for marketability of the target or related devices. As such, much of the initial design, fabrication, and first-level testing is occurring through contractors participating in the U.S. Army SBIR award process (Army Topic #A30-066).

7.3.1 Program Goals

The goal of this project is the development, validation, and use of a phantom device to be used for EEG and/or related equipment based on measuring voltage on the human scalp. Our vision of the device is that it will be conductively analogous to the human brain, skull, and scalp, with different physical layers, and contain multiple (16–32) embedded electrical sources that can be used to simulate signals that are consistent with human brain activity. Finally, because the model will be used as a test fixture within a wide variety of environments and varied conditions, it should be fairly durable, rugged, and portable, requiring minimal maintenance, and be able to survive use within military operational environments.

The end goal is to develop a device that can be used not only for examining and eliminating sources of error and noise within applied-research project environments but also as a standard tool for comparing and validating new EEG technology and algorithms within these or other environments as it becomes available. That is, it will serve as a gold standard for future materials testing.

The overall program is anticipated to include three primary areas:

- Fabrication of a complete head-shaped phantom system. This effort will involve the design and building of a physical system and will inevitably include building several prototype devices and/or subcomponents, as necessary, to determine the appropriate properties, materials, manufacturing methods, and testing procedures for building the final device that meets the necessary requirements. We anticipate the majority of this work to occur external to ARL’s Human Research and Engineering Directorate (HRED) through the SBIR or other external processes, with recurring interaction and feedback from ARL personnel.
- Validation of the device and initial testing. Once prototype devices are developed, they must be validated as indeed having the target qualities (e.g., realistic conductance, durability, etc.) and proven to be usable for ARL’s intended purposes. This effort is

expected to be performed in conjunction with an SBIR contract as well as some testing within ARL, with recurring feedback between the two groups.

- Use of the device as an exemplar test fixture. As initial devices are fabricated and validated, they will be used as test fixtures for various ARL applications, such as assessing ambient (EMI, testing new EEG hardware, or assessing the efficacy of novel signal detection schemes. This testing will serve two purposes: first, to highlight the utility of the device as a useful scientific and engineering tool and second, to provide opportunity for feedback to fabricators for design improvements to ensure maximum efficacy of the device. The majority of this effort will be performed by ARL and collaborating partners.

7.4 Previous Program Activity

7.4.1 SBIR Overview

Effort on this project began in the third quarter (Q3) of FY10 with the solicitation of proposals through the Army SBIR. The primary task of the project was to outline designs and provide evidence of capability to fabricate a physical phantom head-shaped device used for the purposes described previously. Three individual contracts were selected from different groups working independently—CFD Research Corporation (CFDRC), Physical Optics Corporation (POC), and Creare, Inc., with efforts beginning Q2 FY11. All three proposed to deliver a physical prototype device as an example by the end of phase I, but each company placed an emphasis on different aspects of the project and proposed system. A brief review of the efforts and device delivered by each group and ending in Q4 FY11 is outlined in the following sections. Detailed information can be found in the SBIR annual reports.

7.4.2 CFDRC

This project emphasized using computational modeling to derive the appropriate structure and electrical properties for the phantom device; the computational model on which the physical device was based was delivered with the prototype. The delivered model uses a gel-filled cavity as the “brain” inside a plastic mannequin head, with fixed silver epoxy channels to make contact with the surface (figure 7, A). As delivered, the device has an embedded USB-programmable function generator connected to the conductive channels.

7.4.3 POC

POC focused on the material properties and manufacturing process to create realistic conductivity for differing brain/skull/scalp layers. Their approach was a carbon nanotube polymer mixture, where the mixture could be altered to reach the target conductance for each layer. They also focused on identifying a relatively cost-effective manufacturing process. The delivered prototype was a sphere of hard nanotube based polymer, with two embedded electrodes connected to a built-in function generator (figure 7, B).

7.4.4 Creare, Inc.

This contractor, who worked closely with faculty at Dartmouth College, was concerned with having both conductive and physical realism within their prototype model. They completed a series of tests using differing levels of an elastomer mixed with carbon fiber to reach the target realistic conductance, and fabricated a head-shaped prototype based on the magnetic resonance imaging (MRI) of a human (figure 7, C). It includes three separate layers (brain, skull, and scalp) and has 16 embedded electrodes (although several are nonfunctional) and an external function generator, making it fairly universal for different types of testing.

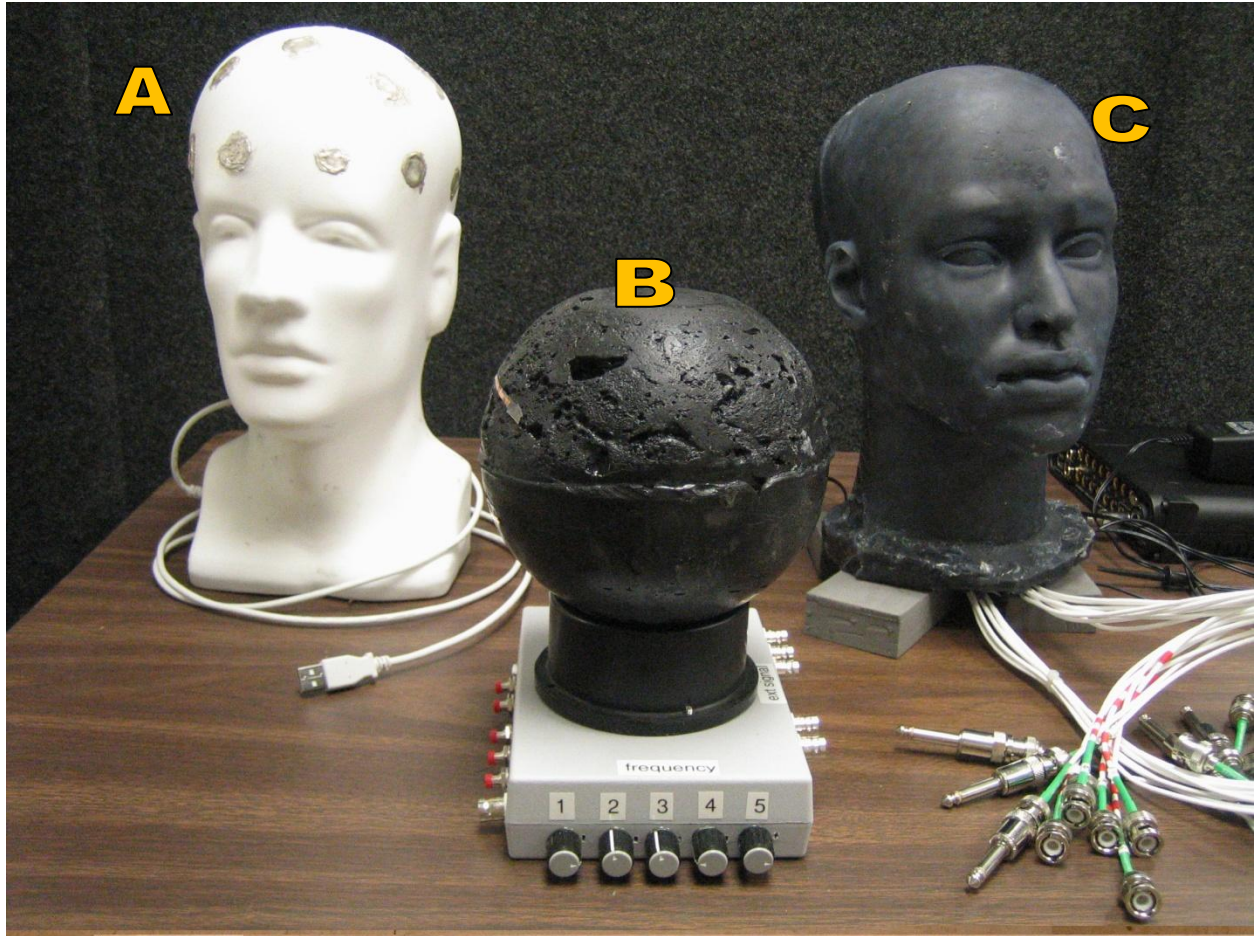


Figure 7. Prototype phantom devices delivered by (A) CFDRRC, (B) Physical Optics Corporation, and (C) Creare, Inc.

7.5 Program Activity During FY12

7.5.1 Fabrication and Validation of Devices

At the beginning of FY12, Creare, Inc., was selected as the primary performer for the SBIR phase II portion of this effort. During the phase I option period, which continued through Q1 FY12, they continued examination into more reproducible long-term viable manufacturing

processes and settled upon a combined three-dimensional (3-D) printing and injection-molding approach as a potential method for future efforts.

However, due to a long-term delay in external contracting, Creare has not yet been awarded the contract for phase II work. As a result, no effort of note has occurred in these areas; all work within ARL has been based on the early prototypes delivered during phase I SBIR efforts in FY11.

7.5.2 Use of Device as an Exemplar Test Fixture

During FY12, the prototype devices were used in a number of applications at ARL, highlighting their utility as a test fixture as well as a means of identifying a number of shortfalls in the current design. The Creare, Inc. prototype was used exclusively. Some examples are:

- Testing timing accuracy in multiple commercial EEG systems. EEG is often collected as a response to particular events, in which case having precise time-marking within the system is critical. We used the phantom head to create a known time-locked signal measured by four different commercially available EEG systems (e.g., figure 8). The variance in accuracy with this data was then compared, yielding the systems that are not reliable for laboratory use. This data effort has been described in Hairston (2012).

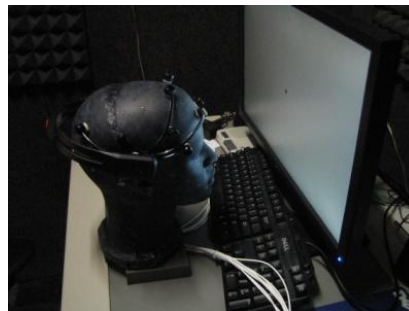


Figure 8. EEG Phantom used as a fixture for testing timing response reliability with a standardized input signal.

- Validation of a timing correction algorithm. Given the high degree of variance and drift observed in actual timing for some EEG systems used at ARL, it was necessary to develop a correction algorithm to compensate for these problems. Once developed, the phantom device was used to provide a known-standard signal to validate the efficacy of the algorithm by comparing the shape of the recorded waveform to the known signal, both with and without correction. This effort has been described in Hairston (2012) and multiple conference presentations including Hairston and Ries (2011) and Hairston et al. (2012).

- Testing timing accuracy in a prototype system. Collaborators at Taiwan's National Chiao Tung University (NCTU), part of the Cognition and Neuroergonomics Collaborative Technical Alliance (CaN CTA) program, have developed new versions of the Mindo EEG headset and related software that are unique approaches to the field. We used the device to determine the timing integration consistency of the new system, and attempted to use it as a standard signal generator. Results showed that the prototype NCTU system has considerable timing errors that must be addressed and that the current design of the phantom is not compatible with the current NCTU hardware approach. We provided this feedback to CaN CTA collaborators.
- Assessing variance in EEG electrode placement across systems. A common problem with different EEG systems is that the actual electrode locations on the scalp may not be consistent across hardware approaches. Because the prototype phantom is modeled from a real human head, it was used as a standard to compare how well each of four different systems actually matched the standard "10–20" locations and estimate how error would be introduced by different head sizes. We discovered that the prototype model is not well suited for this use (due to surface irregularities) and gave feedback to the SBIR contractors at Creare.

7.6 Conclusions and Continuing Efforts

Based on experiences thus far, the phantom EEG devices under development appear to be of practical use for ARL and likely the neuroscience research community as a whole. However, much work remains before a device is available that fully suits the needs of ARL and could feasibly be marketed as a commercial product by the contractor. Overcoming the challenges that have been identified thus far will be the focus of effort over the coming years. Near-future effort in fabrication will focus on materials and construction processes that yield fairly uniform conductivity and proper conductance at the outer skin layer. Additionally, SBIR contractors will be investigating new materials for the inner shell that will enhance stability as well as consistency in production. Meanwhile, efforts within ARL will focus on continued testing and exemplar-use cases of devices, with constant interaction between personnel and contract performers.

7.7 References

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8. Evaluation of Existing Driver Performance Prediction Technologies

8.1 Summary

8.1.1 Introduction

The human operator plays a critical role in vehicle survivability. For example, in civilian and industrial situations, analyses show that human error is at least partly to blame in over 90% of vehicle crashes (Treat et al., 1977). Specifically, fatigue and drowsiness are among the primary contributors to vehicular crashes, which have been found to account for approximately one-third of U.S. military fatalities annually (Krahl et al., 2010). Over the past decade, there have been substantial worldwide research efforts toward developing systems designed to detect and mitigate driver fatigue (Kerick et al., in press). As a result, ARL is researching the development of neurotechnologies designed to enhance survivability through mitigating fatigue-based vehicle operator error, which is the focus of this collective effort.

For years, researchers and clinicians have viewed directly measuring electrical activity from a person's brain through electroencephalography (EEG) as the gold standard in drowsiness and sleep detection. Recent breakthroughs in neuroimaging technology have made using EEG in vehicles feasible, opening the possibility for improving driver fatigue detection technologies., Lin et al. (2005a) attempted to extend these ideas beyond simply detecting the drowsiness of the driver to using EEG to predict driving performance directly. The results showed considerable promise for systems designed to forecast driver error based solely on EEG recordings. While their algorithm was largely effective, the driving scenario they used was highly simplified when compared to military-relevant secure mobility tasks. This current effort focuses on replicating Lin et al.'s (2005a) algorithm to identify areas for enhancement and improvement. It is part of a broader effort to extend this algorithm to more naturalistic driving tasks as well as to other military-relevant situations where vigilance and alertness are imperative.

8.1.2 Methods

During a single 45-min driving session, 14 subjects drove down a long straight highway. Subjects controlled steering and speed and had to observe posted speed limits. Approximately every 10 s, a strong lateral force pushed the vehicle to the left or right. Driver performance was defined as "lane deviation," the distance from the center of the vehicle to the center of the driving lane. Lane deviation was measured continuously at approximately 100 Hz. Throughout the driving session, 64-channel EEG signals were recorded at 2048 Hz. EEG signals were band-pass filtered to the 1- to 50-Hz range and then used to compute the EEG log power-spectrum for 1- to 40-Hz frequency bands. Both EEG spectra and lane deviation were smoothed offline using a retrospective 90-s moving average window, iterating at 2-s steps.

The EEG and lane deviation data were divided into two blocks: a training block (first 15 min) used to train a regression model and a testing block (last 30 min) used to evaluate model performance. Correlation of the smoothed EEG power spectra and lane deviation training data were calculated for each EEG channel and frequency band between 1 and 50 Hz. The two channels with highest average correlation coefficients were selected for principal component analysis (PCA). The resulting PCA scores of the first 50 eigenvectors were used to generate the linear regression for lane deviation. This model was used to predict the lane deviation for the remainder of the session based solely on the power-spectra of the PCA scores of testing data.

Lin's "global" approach trains and tests the algorithm over a relatively long period of time. To compare this approach to one focusing on shorter time frames, we also developed a "local" form of the algorithm that trains on only the previous 60 s of power-spectra and lane deviation and predicts only the next 20 s iteratively across the entire session. This approach may provide greater sensitivity to small or transient changes in the connection between EEG signals and driver performance; however, this added sensitivity may in turn yield erratic predictions for testing data.

8.1.3 Results

In general, the training of the global and local algorithms yielded similar performance to that reported by Lin et al. (2005a) on the training data session, yielding an average correlation of 0.91/0.94 for global/local approaches, respectively. However, performance of both global and local regressions significantly declined when applied to the testing data, yielding respective average correlations of 0.05/0.61. While the performance of the local regression declined significantly less than the global approach, its predictions were generally much noisier and at times resulted in drastic changes in the predicted driver performance.

8.1.4 Discussion

From these results, it appears that the increased complexity of a naturalistic driving task poses a significant challenge to EEG-based driver performance prediction. Nonetheless, we do see a large potential for improving upon these linear regression algorithms. To that end, we are currently investigating several avenues that we have identified as potential means to advance the concept of EEG-based prediction of driver performance:

- Adjusting the width or iteration rate of the moving average window may improve performance by optimizing how much data are combined into a given data point used by the regression.
- Combining the global and local approaches may offer improved performance over either approach individually. Each approach, global and local, offer distinct advantages that if integrated appropriately (e.g., on the basis of their covariances) could provide a more accurate and more stable prediction of driver performance.

- Enhanced behavioral metrics (e.g., eye-tracking/blinking, steering control, time-to-contact of lane boundary) are also being considered. Like lane deviation, these measures have a solid link to driver fatigue, but may also be tied to EEG signals to improve predictive performance.
- To explore improvements to the regression algorithm itself, Support Vector Regression (SVR) is also being used to predict driver performance. SVR has proven to be a highly effective and easily implemented machine-learning approach, and is likely to be more robust to variability in the driver performance metric associated with more complex driving conditions.
- Network connectivity measures are also being explored to assess whether driver performance can be predicted from a combination of EEG electrode sites better than if the channels are considered independently, as in Lin's approach.
- In addition to EEG signals, we have access to multiple other measures that may be used to predict driver fatigue and performance. Measures such as eye-tracking and blinking as well as aspects of steering wheel variability and reversals have been used to predict driver fatigue. Thus, combining these approaches with an EEG-based estimator of driver state/performance may yield a system that out-performs any single-measure-based prediction.
- A multitier classification of driver performance may provide the appropriate level of insight into driver fatigue while also improving predictive accuracy. To investigate this potential, Support Vector Classification (SVC) based approaches to predicting driver performance from EEG signals are also being explored.

8.1.5 Conclusion

Given the encouraging results of the Lin et al. approach described here, we believe that these proposed extensions are likely to facilitate the expansion of their basic method to increasingly more complex driving environments. It is our further hope that the resulting algorithm will have applications beyond the vehicle and be capable of reliably predicting lapses in performance in any task that requires an alert and attentive soldier. See the appendix for additional detail.

8.2 Introduction

Fatigue and drowsiness are among the primary contributors to vehicular accidents, being estimated to have contributed to over 90% of all accidents (Treat et al., 1977). As a result, the prevention of these accidents has become a major focus of driver safety research (for a summary of the major findings in this area, see the review on fatigue technology from Kerick et al. (in press)). This is a particularly relevant issue for today's military, as it has been recently estimated that vehicle accidents account for approximately one-third of military fatalities (Krahl et al., 2010). Unfortunately, many factors contribute to drowsiness or fatigue while driving, including

long working hours, lack of sleep, use of medication, and the nature of the task—for example, long-distance convoy transport. In fact, a 2005 poll conducted by the National Sleep Foundation found that about 60% of adult drivers admitted to getting behind wheel in a drowsy or fatigued state (National Sleep Foundation, 2005). In light of this, there has been a significant push to develop a system capable of detecting driver drowsiness and initiate mitigating strategies to remedy the situation.

Toward this end, many systems have been designed to detect driver fatigue, several of which display relatively good accuracy. Typically, these systems have relied on vehicle-mounted sensors that correlate certain behaviors, such as driver posture or eye-blinking characteristics (Smith et al., 2000; Perez et al., 2001; Popieul et al., 2003). In addition to these behavioral metrics, a number of recent studies have attempted to use EEG signals to predict the onset of driver fatigue and drowsiness. If successful, an EEG-based system may offer important advantages over behavioral measures, such as the ability to predict drowsiness well in advance of its behavioral manifestations, and may be able to quantify the level of drowsiness of a driver as it evolves. Intriguingly and encouragingly, a number of these studies have found significant correlations between neural signals and driver fatigue (for a review, see Lal and Craig, 2001) despite differing widely in their approach, and have led to the development of several algorithms capable of classifying periods of driver fatigue.

Lin et al. (2005a) have attempted to not only determine fatigue onset but directly predict driver behavior based solely on neural activity recorded while driving. To do this, they have applied a linear regression algorithm to EEG signals to predict subjects ability to compensate for vehicle perturbations with impressive results. However, the driving simulation used in their task was very simplistic, and thus it remains unclear if such this regression model would perform adequately in more complex driving tasks or across a wider range of subjects. To begin to address this question, we sought to reimplement the approach detailed in Lin et al. (2005a) to a more realistic driving simulation in which a subject must maintain continuous active control of the vehicle's position and speed while responding to road signs and lateral perturbations of the vehicle.

8.3 Methods

8.3.1 Subjects

A total of 14 subjects (aged from 20 to 40 years) participated in the SVR-based highway driving experiments. Each subject was briefed on the experimental equipment and procedures and signed an informed consent form. Protocol and forms were approved by the Army Research Laboratory human-use board (Project # ARL 10-051).

8.3.2 Experimental Protocol

Subjects completed two separate driving sessions: the first baseline session lasted 15 min and the second experimental session consisted of 45 min of continuous driving. Before each session,

subjects provided an estimate of their fatigue level via the Karolinska Sleepiness Scale (KSS) (Akerstedt and Gillberg, 1990). Additionally, subjects were asked to verbally report their fatigue score on this scale every 15 min during the second experimental session.

Subjects were instructed to keep their vehicle as close to the center of the right-hand lane as possible. After the simulator determined the subjects had been within the appropriate lane for 8 to 11 s, a lateral perturbation was applied to the vehicle, causing it to veer off course and if unabated, out of the lane. The perturbation continued to push the vehicle until the driver made a corrective steering adjustment, defined as a steering wheel deflection of one degree in the opposite direction of the perturbation, at which point the perturbation ceased and the subject was to return the vehicle to center of the driving lane. If the subject did not perform a corrective steering adjustment, the perturbation would ramp down automatically after approximately 3 s; however, it was left to the subject to correct the vehicle's heading and position. In addition to maintaining control of the vehicle's direction, drivers also maintained appropriate speed for the vehicle during the testing session. Subjects controlled their speed via accelerator and brake pedals and were instructed to obey posted speed limit signs that appeared during the driving session. For the majority of the session, the speed limit was 45 mph. At three different points during the testing session, the posted speed limit was reduced to 25 mph.

8.3.3 Data Collection

Vehicle status and performance metrics. Vehicle status, sampled at approximately 100 Hz, was monitored throughout each session. Several relevant measures were recorded, with the present analysis focusing primarily on lane deviation—the distance between the center of the vehicle and the center of the driving lane.

Electroencephalography. EEG signals were collected using a 64-channel Biosemi EEG system, sampled at 2048 Hz. Electrode offset was configured to be less than 25 mV before proceeding with data collection.

Eye tracking. Eye position was monitored throughout the experiment using SensoMotoric Instruments (SMI) eye-tracker, sampled at 256 Hz.

8.3.4 Data Analysis

Vehicle, EEG, and eye-tracker data were collected simultaneously throughout the experiment. Specific event markers were embedded within each data structure and used to align the data in time and remove any drift or jitter in the time series of each data stream.

Lane deviation was used as the primary metric of driver performance over time, as has been used in similar fatigue prediction studies (Lin et al., 2005a). Lane deviation values over the entire session were smoothed using a 90-s moving average filter with 2-s increments. This was advantageous, as use it yields a driver performance metric that illustrates longer scale fluctuations in performance, rather than one which is more susceptible to variability associated

with the task (e.g., the perturbations that artificially increase lane deviation). A similar process was performed on the steering wheel orientation collected during each driving session.

The 64-channel EEG data was collected at 2048 Hz and then down-sampled to 256 Hz. Using the embedded timing pulses and event signals, the EEG time series was synchronized with the vehicle status and driver performance data. Following this, the data was band-pass filtered to remove signals greater than 50 Hz and less than 1 Hz. The data for each channel was then converted into its power spectrum using a 750-point Hanning window with 250-point overlap. Each EEG channel and frequency power estimate of the 1–40 Hz bands was then passed through the same 90-s moving average filter used to smooth the lane deviation data, preserving the temporal alignment of the two data streams. The smoothed lane deviation data was subsequently used as a metric of driver performance and used to train a linear regression model with the simultaneously recorded EEG data used as a predictor of the driver performance metrics.

Performance prediction. The data from the experimental session was split into two subsections, the first 15 min of data reserved for training and the last 30 min of data for testing the driver performance prediction regression. The first step in this was to use the training data to identify the frequency bands in which EEG channels varied most consistently with the measures of driver performance. A correlation analysis was performed between lane deviation data and power estimate for each frequency band for each EEG channel. The top two channels that were on average most positively correlated with driver performance were selected for further analysis. PCA was then performed on the power spectral bands, and the resulting eigenvalues were used to reduce the dimensionality of the EEG feature space from 100 to 50 dimensions.

The data from the training portion of the driving session was projected into principal component space and the first 50 eigenvectors were used as input variables to train a 50-order linear regression. To assess the quality of the fit of the regression model, the same EEG data used to train the regression model was input into the algorithm again to predict lane deviation during the training session. This output was compared to the actual levels of driver performance.

To evaluate the algorithm's ability to predict driver performance, the regression coefficients calculated with the training data was then applied to PCA projections of the EEG data reserved as the testing portion of the session. The predicted values of lane deviation generated by the model were compared to the measured driver performance for each epoch to characterize the predictive accuracy of the approach.

Local vs. global regression. The described algorithm essentially adapts the Lin et al. (2005a) algorithm to our in-house driver simulator. In its original form, the algorithm generates a prediction over a long span of time and is also trained over a long time period; thus, we can consider this a global regression approach. To evaluate the potential of using only the most recent driving behavior and brain activity, we developed a second algorithm that uses

the same regression approach applied to a much narrower space of time. Using only the preceding 60 s of data for training, the algorithm was used to predict the next 20 s of driver performance. This prediction algorithm can then be applied iteratively across the entire driving session to provide a local prediction.

8.4 Results and Discussion

Global regression. Figure 9 illustrates the measured lane deviation (black line) as the predicted values (blue line) produced by using the global form of the Lin et al. (2005a) algorithm for both the training (left) and testing (right) periods of the driving session for a single subject. As expected, strong performance was observed when the regression model is reapplied to the training set, and indeed, this was observed for this subject, yielding a mean-squared error (MSE) measure of 0.001 m and a correlation coefficient of 0.89. Performance decreased sharply when the regression model was applied to the testing set of EEG data, producing a MSE measure of 0.268 m and a correlation coefficient of 0.31.

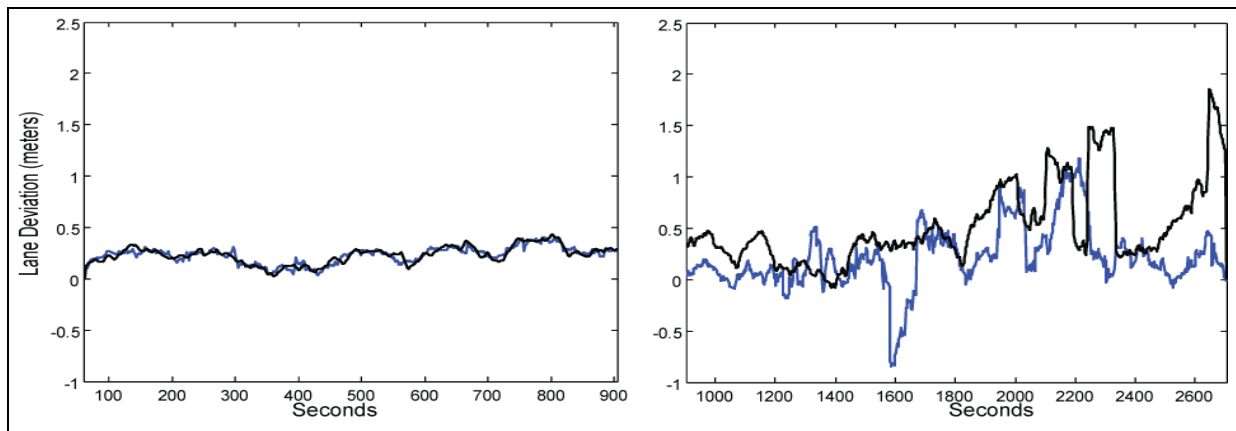


Figure 9. Actual (black line) and predicted (blue line) lane deviation of a single subject using the global form of the Lin et al. (2005) approach. The regression algorithm was used to predict lane deviation of both the training data (left) and the testing data (right) using the training data.

Table 1 relates the performance of the algorithm on both the training and testing data for all the subjects. In general, the algorithm performed well when predicting driver performance from EEG signals during the training period of time. For the 14 subjects, the average MSE of the prediction was 0.002 ± 0.002 m, with an average correlation between predicted and actual lane deviation was 0.91 ± 0.06 . However, when the regression model was applied to portion of the driving session reserved for the testing period, performance declined significantly for nearly every driver. Table 1 provides the prediction accuracy for each subject. Across the population, the average MSE of the prediction for the population was 0.335 ± 0.53 meters with an average correlation of 0.05 ± 0.25 .

Table 1. MSE and correlation coefficients of lane deviation prediction performance for the global and local regression algorithms.

| Driver | Global Regression | | | | Local Regression | | | |
|---------|-------------------|----------|---------|----------|------------------|----------|---------|----------|
| | Training | | Testing | | Training | | Testing | |
| | MSE | Corr (R) | MSE | Corr (R) | MSE | Corr (R) | MSE | Corr (R) |
| 1 | 0.001 | 0.909 | 0.093 | -0.156 | 0.002 | 0.975 | 0.008 | 0.890 |
| 2 | 0.001 | 0.890 | 0.268 | 0.313 | 0.017 | 0.930 | 0.065 | 0.743 |
| 3 | 0.001 | 0.913 | 0.073 | 0.080 | 0.001 | 0.926 | 0.003 | 0.772 |
| 4 | 0.004 | 0.921 | 0.348 | -0.392 | 0.029 | 0.913 | 0.110 | 0.664 |
| 5 | 0.001 | 0.931 | 0.039 | -0.100 | 0.001 | 0.945 | 0.007 | 0.704 |
| 6 | 0.002 | 0.905 | 0.038 | 0.295 | 0.001 | 0.926 | 0.012 | 0.586 |
| 7 | 0.001 | 0.762 | 1.740 | 0.246 | 0.001 | 0.952 | 0.009 | 0.670 |
| 8 | 0.006 | 0.791 | 1.349 | 0.540 | 0.001 | 0.924 | 0.072 | 0.371 |
| 9 | 0.003 | 0.957 | 0.076 | 0.269 | 0.002 | 0.970 | 0.013 | 0.826 |
| 10 | 0.001 | 0.963 | 0.231 | -0.112 | 0.001 | 0.965 | 0.025 | 0.511 |
| 11 | 0.002 | 0.967 | 0.219 | -0.209 | 0.010 | 0.936 | 0.130 | 0.467 |
| 12 | 0.001 | 0.965 | 0.090 | -0.011 | 0.004 | 0.945 | 0.145 | 0.376 |
| 13 | 0.001 | 0.942 | 0.067 | 0.019 | 0.006 | 0.911 | 0.044 | 0.503 |
| 14 | 0.0 | 0.980 | 0.057 | -0.053 | 0.001 | 0.957 | 0.036 | 0.407 |
| Average | 0.002 | 0.914 | 0.335 | 0.052 | 0.006 | 0.941 | 0.048 | 0.606 |

Clearly, there was a considerable decrease in performance in this approach when applied to the testing data. In fact, the decrement far exceeded that observed by Lin et al. (2005a) for their testing data. Thus, it is likely that the added complexity of the present driving simulation is at least partly responsible for poorer regression performance. One potential explanation for this is that in the present experiment, changes in lane deviation may be related to subject-specific driving habits rather than a lack of response to vehicle perturbation due to fatigue. Another possible explanation is that the nonstationary nature of neural signals affects or changes the connection between driver performance and specific elements of the EEG power spectrum over the course of the driving session. If this were the case, one would expect a significant improvement in predictive accuracy when the local regression prediction is factored in.

Local regression. Figure 10 illustrates the measured and predicted values of lane deviation of the testing data using the local form of the Lin et al. approach for the same subject depicted in figure 1. A comparison of the figure 10A with the right-hand plot of figure 9 reveals a marked improvement in the performance of the local vs. the global for the testing data for this subject. This difference was consistent for all subjects, with the local algorithm yielding an average MSE error of 0.006 ± 0.008 m for the training data and 0.048 ± 0.048 m for the testing data, and with respective correlations between predicted and actual lane deviation of 0.94 ± 0.02 and 0.61 ± 0.17 .

Figure 10B illustrates the relationship between the MSE of the prediction in global vs. local algorithms for all 14 subjects. Figure 10C demonstrates a similar comparison between approaches for the correlations of the predicted and the actual behavior. While the global

regression is slightly better when reapplied to the training data, this difference was not significant. Conversely, when applied to the testing data, both the MSE error values and correlation coefficients were significantly different between the two algorithms ($p < 0.05$, Wilcoxon test), indicating significantly better performance of the local regression approach for predicting novel data.

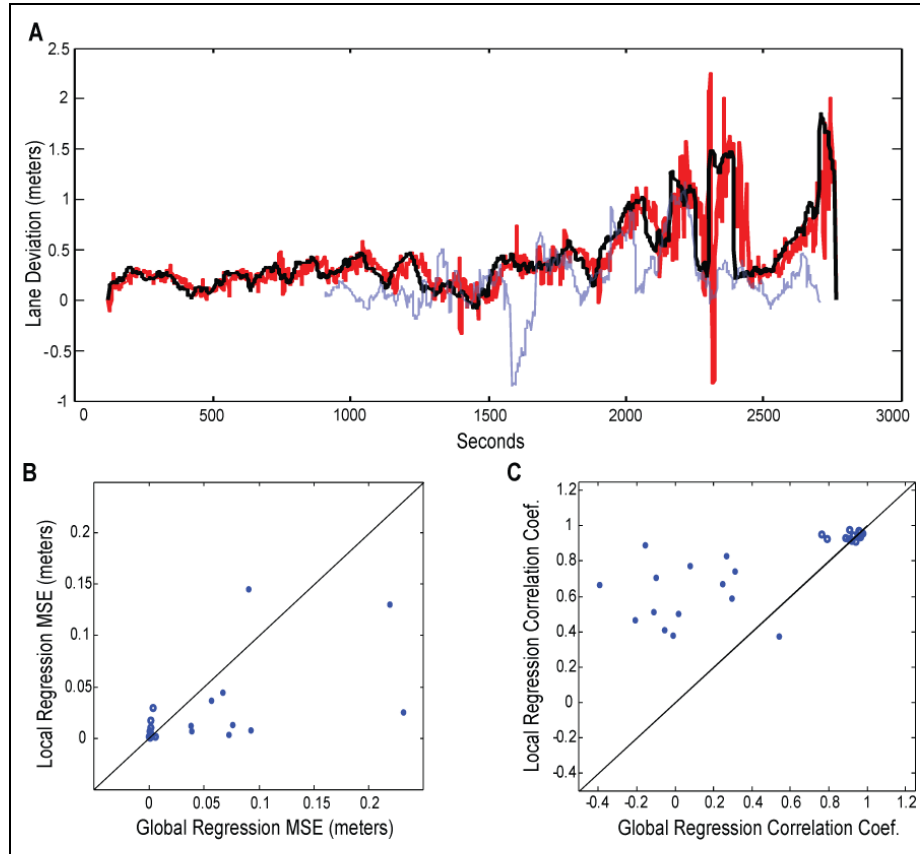


Figure 10. Comparison of local and global regression performance: (A) local regression prediction (red line) and measured values (black line) of lane deviation across the driving session for a single subject. Also visible is the trace of the global regression prediction (grey line). Global vs. local predictions for (B) MSE and (C) correlation with actual driving behavior for all subjects. Open circles represent the training data and closed circles indicate prediction performance on testing data.

The improved performance of the local regression algorithm is likely due to the relative instability of EEG signals, particularly over long time scales, as described. Conversely, because the regression coefficients are constantly being updated to match more recent brain activity with driving performance, the local regression algorithm is able to adapt to and change with the transient nature of EEG signals across long experimental sessions.

Note that the local approach yields a noisier prediction of driver performance (see figure 10A), likely due to an enhanced sensitivity to a limited number of EEG features that may have only

transiently or artificially improved regression during the shortened training period. In contrast, the global regression algorithm appears less sensitive to moment-to-moment swings in EEG features, resulting in a somewhat more stable, if less accurate prediction of driver performance.

8.5 Conclusions

The accuracy of the predicted values of driver performance varied greatly between drivers for both local and global approaches. Encouragingly, regression performance on training data was in general consistent with what was reported in a similar task, however somewhat reduced, indicating that a linear regression model can represent the data reasonably well. On the other hand, average performance on testing data was markedly worse in this study than was reported by the algorithm's original developer. However, it is important to note that direct comparison between results is difficult, as we did not enforce the same exclusion criteria as the original investigators, which allowed them to focus only on those subjects who exhibited severe fatigue. Instead, we considered algorithm performance across all participating subjects. It should also be mentioned that our simulation was designed to be more reminiscent of actual driving, resulting in a more variable measure of driving performance. This increased variability results in fluctuations in the performance that are not necessarily attributable to fatigue or any change in EEG data and potentially adversely affect regression performance.

8.6 Future Directions

From these results, it appears that the increased complexity of naturalistic driving task poses a significant challenge to EEG-based driver performance prediction. The decrease in global regression performance for the testing data is likely due to the increased complexity of continuously controlling vehicle dynamics in this experiment vs. that of Lin et al. (2005a). This is a troubling trend, however, as even the current simulation is still far from representative of the complex environments in which Soldiers must operate. Nonetheless, we do see great potential for improving upon these linear regression algorithms. Toward this end, accounting for the increased variability or changes in performance due to exogenous factors is a primary concern. We are currently investigating several avenues we have identified as potential means to advance the concept of EEG-based prediction of driver performance:

- Adjusting the width and/or iteration rate of the moving average window may improve performance by optimizing how much data is combined into a given data point used by the regression. Increasing the width and iteration rate will stabilize EEG estimates over time but may result in slower estimation of changes in the soldier/driver's state.
- Combining the global and local approaches may offer improved performance over either individually. Each approach, global and local, offer distinct advantages, and if integrated appropriately could provide a more accurate and stable prediction of driver performance.

One approach may be to weight them based on their covariances, as this approach may stem the influence of rapid fluctuations of the local regression.

- Additional or alternative behavioral metrics to lane deviation are being considered. For instance, eye-tracking/blinking, steering control, and time-to-contact of lane boundary all have a solid link to driver fatigue, but might also be more strongly tied to EEG signals. In addition, these measures might be more consistent and resilient to increases in task complexity and may improve predictive performance.
- To explore improvements to the regression algorithm itself, SVR is also being used to predict driver performance. SVR has proven to be a highly effective and easily implemented machine-learning approach, and is likely to be more robust to variability in the driver performance metric associated with more complex driving conditions.
- Network connectivity measures are also being explored to assess whether driver performance can be predicted from the signals from a combination of EEG electrode sites better than if the channels considered independently, as in Lin's approach. Further, insights gained from this analysis may also be useful for identifying alternative behavioral metrics that show a stronger link to EEG signals.
- Alternative feature extraction methods have been proposed based on matching pursuit and wavelet analysis. Examining specific features of EEG signals extracted using these methods may improve performance by feeding only the most relevant signals to the regression model.
- A multitier classification of driver performance may provide the appropriate level of insight into driver fatigue while also improving predictive accuracy. To investigate this potential, SVC-based approaches to predicting driver performance from EEG signals are also being explored. An additional advantage of this tact is that by condensing performance into classes, we reduce a great deal of variability in the performance metric that accompanies increases in task complexity.

In addition to the aforementioned approaches, we are also continuing to work with the developers of the original algorithm. They too have explored alternative approaches, focusing largely on algorithms involving Independent Component Analysis (ICA) (Lin et al., 2005b; Chuang et al., 2012). ICA offers a means to focus on a specific, potentially more salient source of neural activity than channel data.

Given the encouraging results of the original Lin et al. (2005a) approach as applied here, we believe that these proposed extensions are likely to facilitate the expansion of their basic method to increasingly more complex driving environments. It is our further hope that the resulting system will have application beyond the vehicle, capable of reliably predicting lapses in performance in any task which requires an alert and attentive Soldier or agent.

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Appendix. Government Fiscal Year 2012 Outcomes

This appendix appears in its original form, without editorial change.

Data Collections:

Data collection completed for joint ARL-TARDEC TX-18 experiment (section 5).

Data collection completed on ARL study to validate driver performance simulation technologies (section 6).

Funding:

G. Slipher, R. Mrozek, K. Whitaker, W. D. Hairston, and W. Nothwang, “Stretchable Conductive Elastomers for Soldier Bio-Sensing Applications,” U.S.Army Research Laboratory, Director’s Research Initiative, Award #FY13-VTD-009, 2012. Total of \$750,000 in funding across 3 years.

Software:

Simulation software for researching driver performance (section 6)

Continuous Tracking Task for an Android system (section 8)

Psychomotor Vigilance Task for an Android system (section 8)

Proofs/Prototypes:

Physical proof-of-concept EEG stretchable wires system (section 2).

Physical proof-of-concept EEG validation ‘phantom head’ system (section 3).

Physical proof-of-concept of Arduino-based system for synchronizing simulation environments with physiological data collection (section 6).

Published papers and abstracts:

Collier, Thomas J, David B Kynor, Jerry Bieszczad, William E Audette, Erik J Kobylarz, and Solomon Gilbert Diamond. 2012. “Creation of a Human Head Phantom for Testing of Electroencephalography Equipment and Techniques.” *IEEE Transactions on Bio-medical Engineering* 59 (9) (September): 2628–2634. doi:10.1109/TBME.2012.2207434.

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List of Symbols, Abbreviations, and Acronyms

| | |
|---------|---|
| CaN-CTA | Cognition and Neuroergonomics Collaborative Technology Alliance |
| CATS | cognitive avionics tool set |
| CTT | continuous tracking task |
| DARPA | Defense Advanced Research Projects Agency |
| EDA | electrodermal activity |
| EEG | electroencephalography |
| EKG | electrocardiography |
| EMI | electromagnetic interference |
| fMRI | functional magnetic resonance imaging |
| FMTs | fatigue management technologies |
| GVSL | ground vehicle simulation laboratory |
| ICA | independent component analysis |
| ILIR | in-house laboratory independent research |
| KSS | Karolinska Sleepiness Scale |
| MEG | magnetoencephalography |
| NCCF | nickel-coated carbon fibers |
| NCTU | National Chiao Tung University |
| NIH | National Institute for Health |
| PCA | principal component analysis |
| PDMS | poly-dimethyl siloxane |
| POC | Physical Optics Corp |
| PVT | psychomotor vigilance task |
| RMS | ride motion simulator |
| SBIR | small business innovative research |
| TSD | temporal synchronization device |

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